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Reduced rework through data analytics and machine learning – a three level development approach

Lukas Longard[a,*], Felix Brungs[b], Christian Hertle[c], Jochen Röth[c], Joachim Metternich[a]

[a]*Institute of Production Management, Technology, and Machine Tools, Otto-Berndt-Str. 2, 64287 Darmstadt, Germany*
[b]*MAN Truck & Bus, Dachauer Str. 667, 80995 München, Germany*
[c]*SFM Systems, Hilpertstraße 31, 64295 Darmstadt, Germany*

Abstract

In many production companies, rework of products that do not meet the defined quality level is a common practice. Usually organized at the end-of-line in form of test and rework cycles the goal is that no defect "escapes" to the customer. Only in rare cases, a systematic problem solving is triggered through a rework process to identify and remove the root cause. In the EIT Manufacturing project IVE a data-driven problem-solving tool is being developed with the focus on rework. Through a three-level development approach, the goal is to significantly reduce rework effort as well as the time to detect and analyze a problem. In the first level, an error score is being developed to give the shop floor team an overview about error clusters and to help them decide which errors to focus on. In the second level, machine learning is used to give action recommendations to the rework teams and to predict the needed work force depending on the production program. In contrast to the first two levels, which aim to reduce the amount of rework, the third level aims to completely avoid rework through in-line action recommendations based on data from preceding processes. To validate and demonstrate the usefulness of a data-driven approach as well as the implementation of machine learning algorithms to companies, the developed tool will be implemented in the "process learning factory CiP". For this purpose, a rework station will be created and designed to meet the specific needs. If the implementation is successful, the concept can also be transferred to other learning factories.

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1. Introduction

The rapid identification and resolution of quality problems in production is becoming increasingly important due to ever more complex processes. In highly automated production processes a lot of data is available, but due to the amount of data, manual analysis commonly done with spreadsheet applications is not efficient and hardly useful. Therefore, using automated data analytics and machine learning, possible root causes can be identified faster, and action recommendations can be given.

Until corrective actions are implemented, rework is still required, or at least preventive actions are necessary to avoid customer complaints. While machine learning models are often used to support many quality processes, the rework processes often remain unaffected. However, it is the analysis of detailed error descriptions as well as error corrections that offers the potential to set the right focus to identify and sustainably eliminate the causes of problems. This paper proposes a three-level approach to significantly reduce rework through data analytics and machine learning and shows first results from evaluations and implementations in practice and the process learning factory CiP.

* Corresponding author. Tel.: +49 6151 16-20121
E-mail address: l.longard@ptw.tu-darmstadt.de

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2. State of the art

2.1. Shop floor management and its digitalization

Shop floor management is widely used in industry to lead workers on the shop floor and support them with continuous improvement activities. Studies from Germany show that in 2018 more than 80% of producing companies used shop floor management as a daily management tool compared to 67% in 2016 [1,2]. Although not uniformly defined, several publications describe shop floor management as a deviation management method that makes use of the following fields of activity [2,3]

- performance management: KPIs, target states, and detect deviations
- problem-solving: description, root-cause-analysis, solution planning and PDCA
- leadership: process confirmation, gemba walks, leader standard work
- glass wall management: mini factory concept, creating transparency
- competency management: qualification of workers, staffing.

The digitalization of shop floor management seeks to enhance these fields of activity and analyze the data for further insights. Through real-time data availability deviations can be detected earlier and more precise. Moreover through predictions of KPIs countermeasures can be induced before an deviation causes a defect [4]. Via prioritizing deviations, problem-solving activities can be more channeled and thus more effective. Furthermore, applying predictions to tasks and problem-solving highlights critical tasks and helps leaders and workers focus on them. Altogether they lead to comprehensive digitalized shop floor management: the digital shop floor management [5,6].

2.2. Rework

Production processes are imperfect and due to influences caused by material, technology, operators and environment rework becomes necessary [7]. Rework situations in flow production environments can be differentiated by in-line and off-line rework (see Fig. 1). At in-line rework, the same resources (men, machines, and tools) are used for regular production as well as for rework which is supported by “jumper”-operators. The goal is to identify and fix quality problems within the production line. If this is not possible (e.g. due to short customer takt), rework has to be done off-line in a specific rework area. To ensure the customers get products in the right quality, the rework is done by highly qualified operators. Especially the in-line approach is challenging for flow production of customer specific products, as replacement parts must be delivered at the right time to the right position in the line. Because the necessary rework actions and the position in-line are only predictable for already known quality problems, most of the unpredicted problems must be reworked off-line, which causes higher lead times. [7]

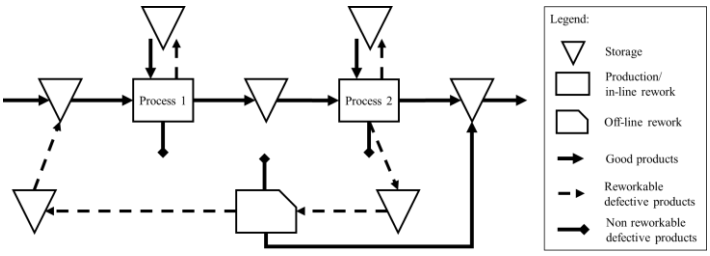

Fig. 1. Production situation with two production-test stages, in-line and off-line rework, and disposal [7]

Rework also plays an important role in the topic of problem solving. Rework activities are taken as an immediate action to secure that no defect “escapes” to the customer. This concerns defective parts as well as ensuring the ability to deliver on time [8]. Since immediate measures are seldomly planned, they result in high costs. In this context, the rule of ten is often mentioned. It states that troubleshooting costs increase by a factor of 10 downstream in the process [12]. Despite the high cost of rework and the resulting relevance for the industry, standards and support by digital tools have hardly been explored so far.

2.3. Data analytics and machine learning

Examples of data analytics and machine learning can be found in many areas of manufacturing [9]. The methods range from supervised techniques such as fault detection or classification to unsupervised methods like clustering

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of product properties [10,11]. As part of data analytics, applications in practice, statistical approaches like pareto distributions are used for prioritizing rework. It turns out that a pareto distribution provides a better fit to the data than Gaussian distributions, which is normally used. Therefore, the pareto principle is a powerful tool in today's lean manufacturing approaches [12]. The special feature of the data in the rework is their free-text nature (qualitative data). This makes them difficult to interpret by machines and requires advanced approaches such as natural language processing. Today, there is hardly any literature about methods that combine quantitative and qualitative data analysis approaches. The aim of this work is to improve the existing pareto approach and to include qualitative text data.

3. A three-level approach

Considering the developments in shop floor management, problem-solving processes, and manufacturing analytics, the question in the EIT Manufacturing research project "Prescriptive Production Assistant" is therefore:

"How can data in companies be linked to rework in order to reduce the high costs and support employees in their daily work?"

To answer this research question, a problem-driven approach has been chosen. Based on the analysis of the rework areas at two automotive companies, together with a literature review, the following problems are identified:

- Difficulties with identification of error clusters and prioritization of relevant topics
- Difficulties with planning of resources
- High throughput times in rework
- High competencies are necessary and therefore long training phases for new employees
- No learning from solved problems

Originated on the identified problems, a three-level approach to reduce rework through data analysis and machine learning is developed. The novelty of this approach lies in the merging of quantitative (e.g. machine & process data) and qualitative data (rework documentation) by adapting data analytics and machine learning methods. In the following subchapters the three levels are explained in detail.

3.1. Level 1: Prioritize

The analysis at the companies showed that they struggle with the prioritization of relevant topics from the rework areas and often do not know where to start problem-solving activities [13–15]. To overcome this issue, pareto charts have been used to identify the most important errors based on the frequency of their occurrence. The downside of this approach is the nature of the data collected in the rework. The documentation of rework is often done in free text fields. Simply forming categories by hand causes loss of information due to the limitation of endless categories [16]. Therefore, the error score has been developed to use the advantages of pareto charts and specifically address the disadvantages due to information loss or the sole focus on one feature (e.g. frequency of occurrence). For each product to be produced (from the production plan of the next day) in combination with all error combinations that have occurred in the past (error location and type), a score is calculated that indicates how likely each error is to occur. This will be displayed and discussed in the shop floor management (see Fig. 2).

To build the score, explanatory features had to be selected from an existing data collection and a model that represents the production and rework process had to be created. This resulted in a feature selection that represents the attributes product family, date of error occurrence, error location, error type and rework duration as meaningful features. To find out which errors are more relevant to the current shop floor shift than others, a model with three categories was developed:

- **Total time effort (**$S_{total\ time\ effort}$): Consists of two parts. The first, "Frequency of Occurrence" is based on a pareto approach and counts the previous occurrence of an error. The second part, "Time Effort Rework" is the average rework time per defect. Both parts are multiplied.
- **Trend** (S_{trend}): Evaluates whether error appearance has increased during the most recent period of production. To accomplish that, the score calculates the ratio between the average time of rework for given time range and the occurrence of another given time period before that. Additionally, all errors that are calculated to have a decreasing occurrence get a score of 0.
- **Infrequency** (sporadic): Evaluates whether the error has occurred in a given number of the last days. It also checks whether the error did not occur before this period. This period is defined as well. Both time corridors

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are added and checked if the error occurred more than once before. If this is the case and the rework time is greater than the average rework time of all errors of this product family, this error is shown as sporadic. This score is calculated separately, and the results are later added to the actual error score.

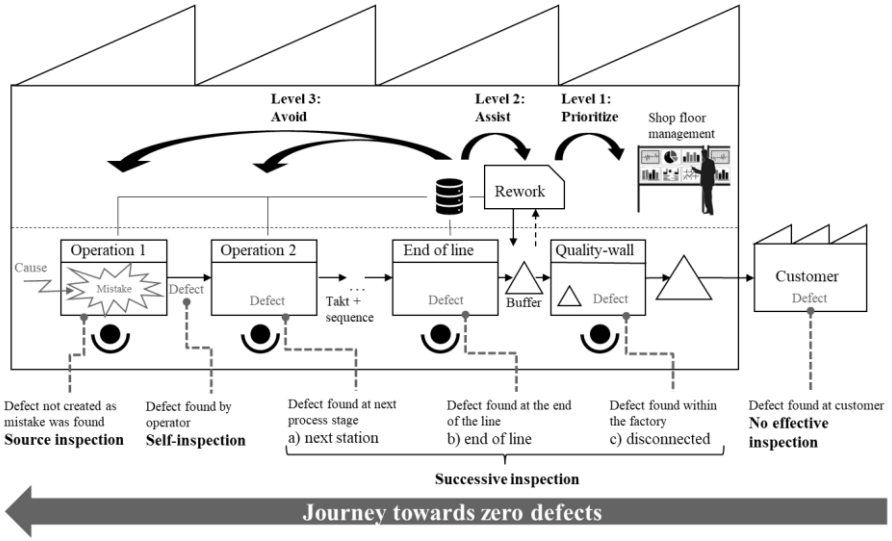

Fig. 2. Three-level approach on the journey towards zero defects

All terms were normalized to values between 0 (min value) and 1 (max value) using a linear min-max normalization. The model is designed to calculate an error score for the entire production data as well as for individual product family. The distinction between product family and product assumes that certain defects occur more frequently for a certain product family than for other product families. This could be empirically confirmed by the available data. To make the generic error score model flexible, weights (w_1, w_2) were introduced to best fit the error score to company-specific data. The weights are adjusted to the available dataset with an optimization procedure. To optimize the values of the weights w for a non-differentiable objective function, the Nelder Mead algorithm is used. To maximize the saved rework time, the error score is multiplied by the rework time of the error in the following week and added up over all errors and their duration. The error score (S_{final}) is calculated as follows:

$$S_{final} = \frac{S_{total\ time\ effort} \cdot w_1 + S_{trend} \cdot w_2}{w_1 + w_2} \quad (1)$$

3.2. *Level 2: Assist*

Based on the prioritization, two different assistance functions are currently being developed in the second level. The first assistance function aims to shorten throughput times in rework by supporting the employee in both troubleshooting and solving the problem through recommended actions (see Fig. 2). In addition, a knowledge management system is to be established through this learning recommendation system, which enables learning from problems that have already been solved and thus shortens the long learning phases of new employees [17,18]. The second assistance function is not intended to directly support the rework process, but rather to facilitate capacity planning. The difficulty in planning for errors that occur and the resulting rework activities poses a major problem for rework capacity planning [17,19]. While overcapacities are cost-intensive, capacity bottlenecks entail further problems like inventories, lack of space, and failure to meet delivery times [15,18].

The goal is to predict the error location and type as well as the necessary time effort for rework based on process and test data from the line together with the planned production program. The predictions of the ML algorithm are fed back to the worker in the form of recommended rework actions via a user interface. In developing the levels, a special focus was placed on a human-centered approach. The algorithm's recommendations are not intended to replace the thinking power of employees, but to supplement it. Here, an active learning approach is taken, where the recommendations of the ML model are either confirmed or corrected / rejected by the employee.

3.3. Level 3: Avoid

While the first two levels aim to improve successive inspection, the third level is intended to support both self- and source inspection. This is based on the lean management philosophy of “zero defects” [20] and aims to

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completely avoid rework efforts. Due to the complexity of manufacturing systems and the high mix of product variants, in-line workers cannot focus on all critical errors at once. To prevent rework issues from occurring at all, these in-line workers need information support during the work process. Therefore, the third assistance function combines data about the manufacturing programme with critical errors caused at different line segments. Based on this, in-line workers get notifications about upcoming product and error combinations and information on how to avoid these errors (see Fig. 2). Through identifying potential errors from historic data and mapping these errors to workstations within the assembly line, the workers attention can be drawn to these critical errors.

4. Implementation

4.1. Evaluation of Level 1

The model was developed from a data-driven process. The starting point is the production data from the project partner MAN Truck & Bus. This dataset contains the documentation of errors occurring in the rework station of MAN rear axle production from January 2019 to December 2019. To simulate the implementation of the algorithm in shop floor meetings, the data set was divided into a training, validation, and unseen test data set. With the training dataset, relevant features were identified and the model itself was developed. The training dataset covers the period from January 2019 to October 2019. The optimization of the weights was conducted using the November 2019 validation dataset. The sporadic score works in parallel and highlights only about four defects per month. If these errors are not already included in the scoreboard, they are simply added, increasing the number of issues.

The algorithm was tested with data from the first week of December 2019. For this, the results are compared with real occurrences in the next 3 days. Not all errors detected by the algorithm occur in this period. In the first week of December, a total of 24 different errors occurred. For this period, the model predicted 7 different errors. Whereby some errors are predicted for several days, 5 of the 7 predicted errors occur in the test data. During the test period, there was a total of approximately 34 hours and 10 minutes of rework on the production lines. Almost 20% (6 hours and 42 minutes of rework time) of the errors were predicted by the model before they occurred. Additionally, raised awareness could be achieved for another 25% of the errors, which means they were detected by the model during the test period, but occurred before they were mentioned. 55% of rework time belongs to 19 different errors not mentioned by the model.

4.2. Evaluation of Level 2

A data set from a different industrial company was selected for the evaluation of level 2. From a car assembly line, the data of 3207 vehicles were collected, with each vehicle forming an instance. As input data (features), the data of the test system in the line were selected. The test data were labeled with the data from documentation of the final rework station (output data). Since the number of instances (3207) was not significantly larger than the number of features (1719 different tests), a dimension reduction to 100 features was performed by an autoencoder to avoid overfitting. After a preliminary study, random forest turned out to be the best method and was used for the classification model. Table 1 shows the results of the model on the data set of the application partner. The results continue to indicate a strong overfitting of the model (training accuracy >> test accuracy). Nevertheless, the results are already promising. With 515 (22) different classes of error location (error type), 35% (55%) are predicted correctly. To counteract the worse performance on the test set (in comparison to the training set), the features will be further reduced in the future. Moreover, classes with the same content are to be recognized and combined by natural language processing to reduce the number of unique classes. Initial tests with manual assignments of errors to classes already show promising results.

Table 1. Accuracy of ML-model.

	Accuracy	
(Train/Test)	Before dimensionality reduction	After dimensionality reduction
Error location (515 classes)	0.87/0.36	0.87/0.35
Error type (22 classes)	0.93/0.51	0.92/0.55

4.3. Implementation at process learning factory

To validate and demonstrate the usefulness of the developed approach and additional to the implementation at two industry partners, the three levels will be implemented step by step in the learning factory “Center for industrial Productivity” at the TU Darmstadt. Until now, the first level could already be implemented completely, and the

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other levels will follow. To prepare for the implementation, the existing value stream had to be adapted. In detail, a new workstation had to be created at the end of the assembly line and the digital worker assistance system already in use had to be expanded to include deviation and rework documentation. The performance of the developed algorithms depends essentially on the initial data basis. Due to the lack of continuous production in the learning factory (approx. only once a month), it was not possible to draw on real data. Therefore, synthetic data were created based on the characteristics of the industrial data sets. In the final step, the newly developed tool was integrated into the existing shop floor management workflow. For this purpose, a new dashboard was designed to present the most important topics from a rework perspective and enable a targeted discussion and derivation of measures. The experience and content gained will be integrated into the workshops of the learning factory and the demonstrator will be used as a showcase for guided tours. The goal is to reduce fears regarding the use of AI and ML through specific, easy-to-understand use cases and to demonstrate the potentials of data mining for industry.

5. Conclusion and Outlook

In many companies, the potential from learning from quality problems remains untapped, especially in rework processes. Based on problems identified from literature and practice, a three-step approach was presented and subsequently evaluated in this paper. The three-level approach showed the expected potential for data analytics and machine learning methods used for predictions of quality related systems behavior. The quality issues predicted by the algorithms had a high accordance compared to errors occurring. A challenge in industrial environments is the quality of the analyzed data. Especially quality related information is often recorded manually, the words used, the description done and even the correct spelling vary from person to person. Therefore, future research projects should focus on the development of filters that identify and normalize the errors described to increase the data base used for data analysis and to get closer to reality with the systems models used.

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References

[1] Pötters, P., Schindler, P., Leyendecker, B., 2018. Status quo Shopfloor Management. ZWF 113 (7-8), 522–525.
[2] Zetmitzsch, G., 2016. Studie zu Anwendungsbereichen von Shopfloor Management Systemen. Master Thesis. TU Darmstadt, Darmstadt, 70 pp.
[3] Hertle, C., 2018. Shopfloor Management Systeme zur zielgerichteten, systematischen Kompetenzentwicklung in der Produktion, 1. Auflage ed. Shaker, Aachen, 169 pp.
[4] Lanza, G., Hofmann, C., Stricker, N., Biehl, E., Braun, Y., 2018. Auf dem Weg zum digitalen Shopfloor Management: Eine Studie zum Stand der Echtzeitentscheidungsfähigkeit und des Industrie 4.0-Reifegrads, 68 pp.
[5] Longard, L., Meissner, A., Müller, M., Metternich, J., 2020. Digitales Shopfloor Management - Wohin geht die Reise? ZWF 115 (9), 645–649.
[6] Meißner, A., Grunert, F., Metternich, J., 2020. Digital shop floor management: A target state. Procedia CIRP 93, 311–315.
[7] Flapper, S.D.P., Fransoo, J.C., Brockmeulen, Rob A. C. M., 2002. Planning and control of rework in the process industries: a review. Production Planning & Control (13), 26–34.
[8] Jung, B., Schweißer, S., Wappis, J., 2020. 8D - Systematisch Probleme lösen, 4. Auflage ed. Carl Hanser Verlag GmbH & Co. KG, München, 128 pp.
[9] O'Donovan, P., 2015. Big data in manufacturing: a systematic mapping study. Journal of Big Data 2 (1), 1–22.
[10] Escobar, C.A., Abell, J.A., Hernández-de-Menéndez, M., Morales-Menendez, R., 2018. Process-Monitoring-for-Quality — Big Models. Procedia Manufacturing 26, 1167–1179.
[11] Escobar, C.A., Morales-Menendez, R., 2018. Machine learning techniques for quality control in high conformance manufacturing environment. Advances in Mechanical Engineering 10 (2), 1-15.
[12] Simpeh, E.K., Ndihokubwayo, R., Love, P.E., Thwala, W.D., 2015. A rework probability model: a quantitative assessment of rework occurrence in construction projects. International Journal of Construction Management 15 (2), 109–116.
[13] Gewohn, M., Usländer, T., Beyerer, J., Sutschet, G., 2018. Digital Real-time Feedback of Quality-related Information to Inspection and Installation Areas of Vehicle Assembly. Procedia CIRP 67, 458–463.
[14] Kamiske, G.F. (Ed.), 2013. Handbuch QM-Methoden: Die richtige Methode auswählen und erfolgreich umsetzen, 2., aktualisierte und erw. Aufl. ed. Hanser, München, 910 pp.
[15] Kropik, M., 2009. Produktionsleitsysteme in der Automobilfertigung. Springer, Berlin, 417 pp.
[16] Sarkar, A., Mukhopadhyay, A.R., Ghosh, S.K., 2013. Issues in Pareto analysis and their resolution. Total Quality Management & Business Excellence 24 (5-6), 641–651.
[17] Krzoska, S., Eickelmann, M., Schmitt, J., Deuse, J., 2017. Data Mining zur Nacharbeitsdauerprognose: Prädiktive Nacharbeitssteuerung und Arbeitsprozessoptimierung für die Montage in der Automobilindustrie. Werkstattstechnik online 107, 773–778.
[18] Werthmann, D., Lappe, D., Otterstedt, N., Scholz-Reiter, B., 2012. Ortungsgestütztes Produktionsleitsystem für die Nacharbeit bei Automobilherstellern. Werkstattstechnik online 102 (3), 114–119.
[19] Ziegler, S., Braunreuther, S., Reinhart, G., 2019. Process Mining zur dynamischen Wertstromaufnahme. ZWF 114 (6), 327–331.
[20] Liker, J.K., Meier, D., 2006. The Toyota way fieldbook: A practical guide for implementing Toyota's 4Ps. McGraw-Hill, New York, 475 pp.

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